Dynamic Airline Fare Optimization Simulation

Trevor Ruggeri

December 12, 2024

Contents

1 Introduction **2**

2 Initial Simulation Results **3**
- 2.1 Tickets Sold and Fare Bucket Revenue . . . 3
- 2.2 Price and Demand Paths (Initial Trial) . . . 4
- 2.3 Total Revenue . . . 4

3 Increasing Initial Prices to Lower Demand **4**
- 3.1 Tickets Sold and Fare Bucket Revenue . . . 5
- 3.2 Price and Demand Paths (Initial Trial) . . . 5
- 3.3 Total Revenue . . . 6

4 Improving Price Responsiveness **6**
- 4.1 Shrinking the Price Adjustment Threshold . . . 6
- 4.2 Decreasing the Alpha Value . . . 7

5 Final Simulation Results **8**
- 5.1 Ticket Sales and Revenue Histograms . . . 8
- 5.2 Final Revenue Distribution . . . 9

6 Conclusions and Improvements **9**
- 6.1 Calibrating Base Demand with Real-World Data . . . 9
- 6.2 Rethinking Initial Price Selection . . . 9
- 6.3 Enhancing the Repricing Logic . . . 10
- 6.4 Machine Learning-Based Price Adjustment . . . 10
- 6.5 Fare Bucket-Specific Pricing Strategies . . . 10

7 Next Steps and Extensions **10**
- 7.1 Exploring Multi-Flight or Network-Level Pricing . . . 10
- 7.2 Incorporating Cancellations and Rebookings . . . 10

Abstract

This report summarizes an iterative Monte Carlo simulation approach in Python for dynamic airline fare pricing. The model incorporates exponential demand elasticity, multiple fare buckets, and adaptive pricing mechanisms. Over multiple trials, we refine our price adjustment method to improve realism and optimize revenue outcomes.

While helping to provide a base understanding as to the process of airfare pricing, this project serves largely as an introduction to the matter. In the final two sections, several different enhancements and next steps are discussed which could improve simulation effectiveness.

1 Introduction

The goal of this project is to examine how Monte Carlo simulations can be used to study a dynamic repricing algorithm for plane tickets. To simplify matters, we postulate a flight departing in 30 days with four different seat types:

1. Economy basic with a 40 seat capacity starting at $250
2. Economy flex with a 30 seat capacity starting at $300
3. Premium with a 20 seat capacity starting at $500
4. Business with a 10 seat capacity starting at $800

We assume Gaussian day-dependent base demand curves for each of the ticket types, with peak demand at different times dependent on the ticket prices. Cheaper tickets are assumed to have peak demand earlier in the 30-day window, while more expensive tickets are assumed to have peak demand later in that window.

Each day, 100 potential customers per fare bucket are simulated. We use an exponential demand model to determine the demand for each ticket type, with different elasticities for different fare buckets. We assume that demands for cheaper-fare tickets have higher elasticities, while demands for the more expensive tickets have lower elasticities. Then, this demand is converted to a purchase probability for each customer, and a random sample in $(0, 1)$ is taken to determine if the purchase is made.

At the end of each day, we look at the ratio of the number of purchases that actually occurred to the expected number of purchases that day, calling this fraction the `pressure`. If `pressure` falls in the range $[0.75, 1.05]$, the ticket price is kept the same. If `pressure` is above this range, we raise prices to accommodate. Similarly, if `pressure` is below this range, we lower prices to account for the slowing demand.

At the end of thirty days, the total number of tickets sold and revenues generated in each fare bucket are tallied, as well as the total revenue over all ticket types. This process is then repeated 1000 times to give us some insight as to average ticket sale and revenue behavior. The price and demand curves for the first trial are also recorded to see how they move under the conditions provided.

2 Initial Simulation Results

In the initial simulation:

- All fare buckets sold out in every trial.
- Prices for economy basic and economy flex experienced little to no movement, indicating that all tickets sold out either immediately or after one day.
- Very low standard deviation in total revenue indicated the same thing – initial prices were too low so everything sold out almost immediately when demand reached a high enough level.

2.1 Tickets Sold and Fare Bucket Revenue

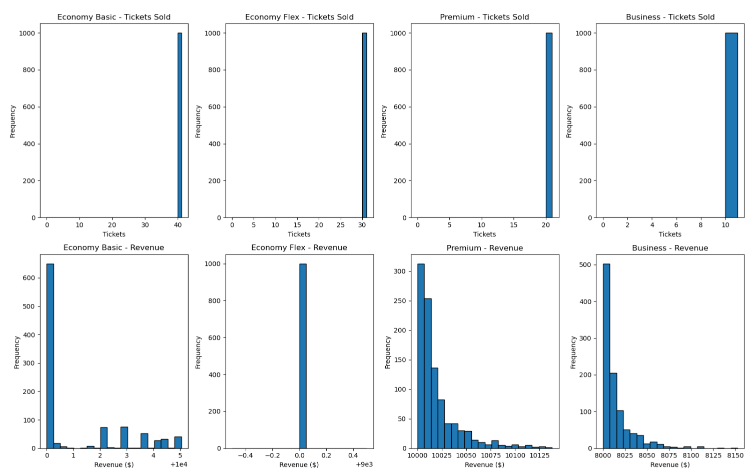

Figure 1: Initial ticket sales and revenue distributions across fare buckets.

2.2 Price and Demand Paths (Initial Trial)

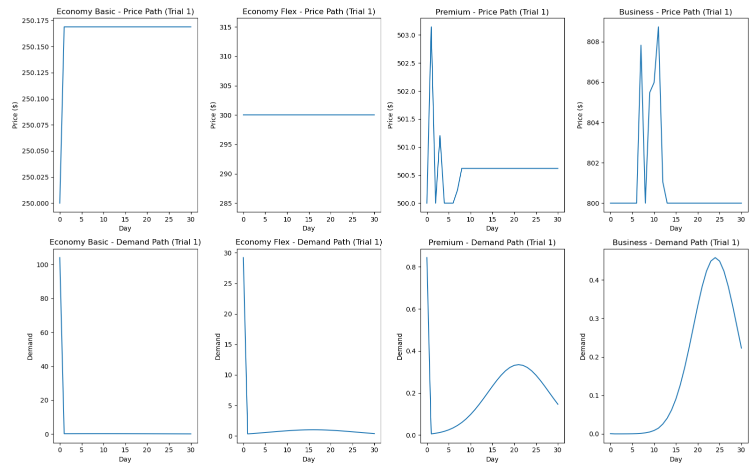

Figure 2: Initial price and demand evolution (Trial 1). Prices did not respond significantly.

2.3 Total Revenue

Under these conditions, the Monte Carlo simulation resulted in

- Mean Revenue: \$37034.46
- Median Revenue: \$37026.03
- Standard Deviation Revenue: \$30.39

The total revenue histogram showed strong performance, but the lack of price movement implied the model was underreacting to demand.

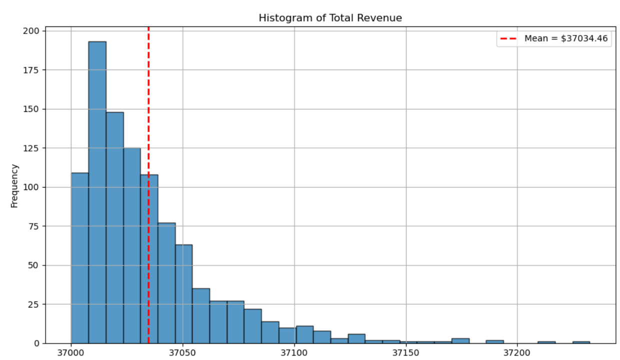

Figure 3: Histogram of total revenue in initial simulation (red line: mean revenue).

3 Increasing Initial Prices to Lower Demand

From the first simulation, we can see that every fare bucket sold out in every trial. Since price shifts were not common in any ticket type, demand under these initial price conditions was too high. To account for this, we need to increase initial ticket prices to decrease demand.

We change the initial ticket prices to the following:

1. Economy basic starting at \$355
2. Economy flex starting at \$585
3. Premium with a 20 seat capacity starting at \$825
4. Business with a 10 seat capacity starting at \$1615

3.1 Tickets Sold and Fare Bucket Revenue

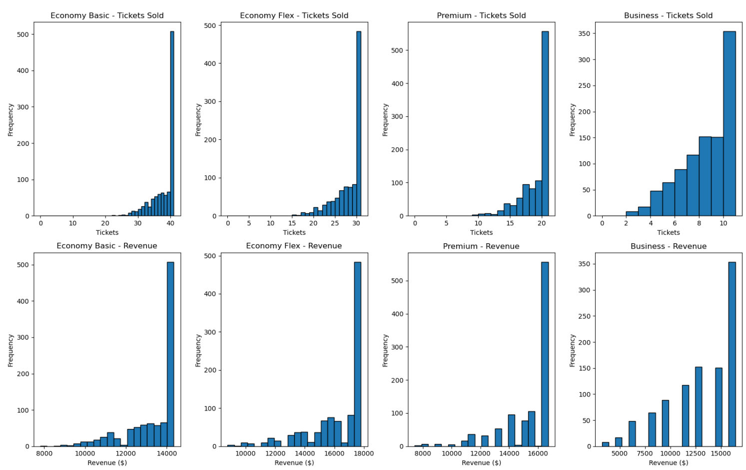

Figure 4: Ticket sales and revenue distributions across fare buckets.

3.2 Price and Demand Paths (Initial Trial)

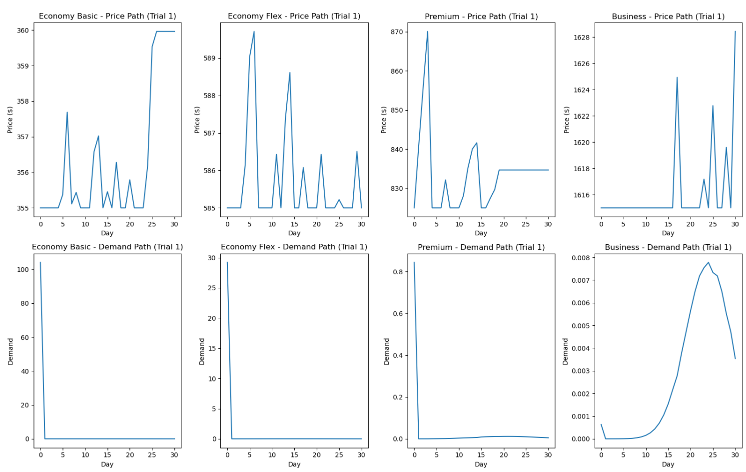

Figure 5: Price and demand evolution (Trial 1).

3.3 Total Revenue

Under these conditions, the Monte Carlo simulation resulted in

- Mean Revenue: \$57882.34
- Median Revenue: \$58615.53
- Standard Deviation Revenue: \$4462.27

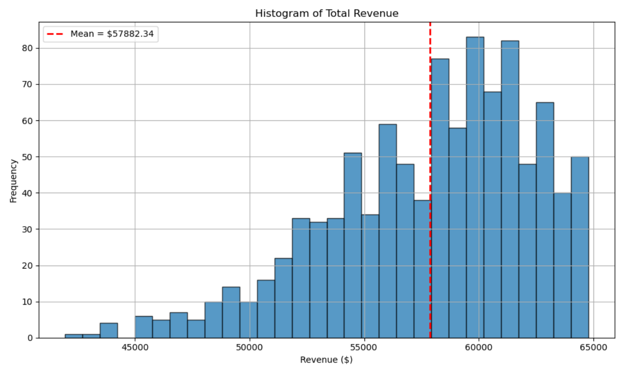

Figure 6: Histogram of total revenue in second simulation (red line: mean revenue).

The revenue improved drastically under this model. However, from Figure 5 it is clear that the price shifts might be too large, as every price jump is immediately followed by a price drop. Next, we will examine how we can lower the magnitude of these shifts in our repricing algorithm.

4 Improving Price Responsiveness

4.1 Shrinking the Price Adjustment Threshold

We reduce the size of our target daily purchase rate range from $[0.75, 1.05]$ to $[0.98, 1.1]$.

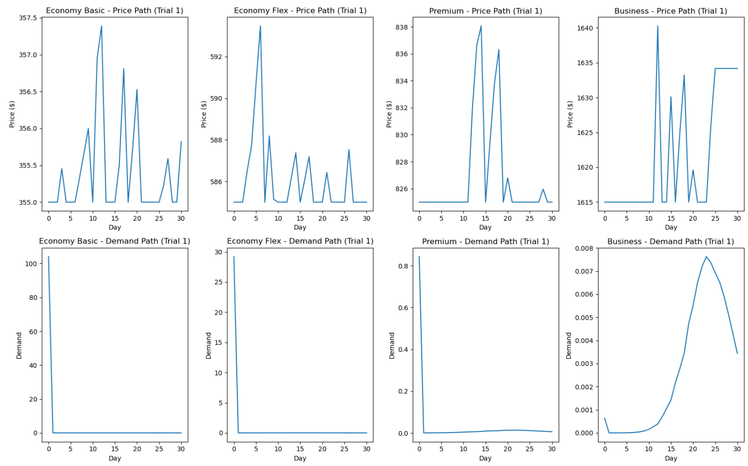

Figure 7: Price and demand paths with lower threshold sensitivity. Price movements decrease in magnitude.

This worked to lower the magnitude of price changes in our repricing algorithm, however the resulting revenue statistics remained largely the same over the 1000 Monte Carlo trials:

- Mean Revenue: $57841.23
- Median Revenue: $58307.27
- Std Deviation Revenue: $4466.47

4.2 Decreasing the Alpha Value

To avoid extreme volatility, we reduce our `alpha` parameter in the price adjustment formula, a scaling factor applied to the `pressure` ratio used in increasing/decreasing the ticket prices, from $\alpha = 0.005$ to $\alpha = 0.001$.

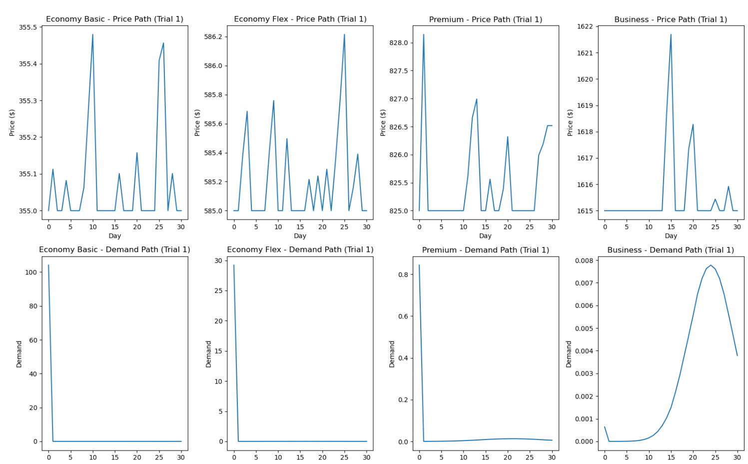

Figure 8: Paths with alpha reduced moderately. Price smoothness and realism improved.

5 Final Simulation Results

Under these conditions, we saw the following total revenue statistics over the entire Monte Carlo simulation:

- Mean Revenue: \$58001.17
- Median Revenue: \$58288.99
- Standard Deviation Revenue: \$4204.20

The following histograms display the seats sold and revenues for the individual fare buckets, as well as the total revenues over the 1000 trials.

5.1 Ticket Sales and Revenue Histograms

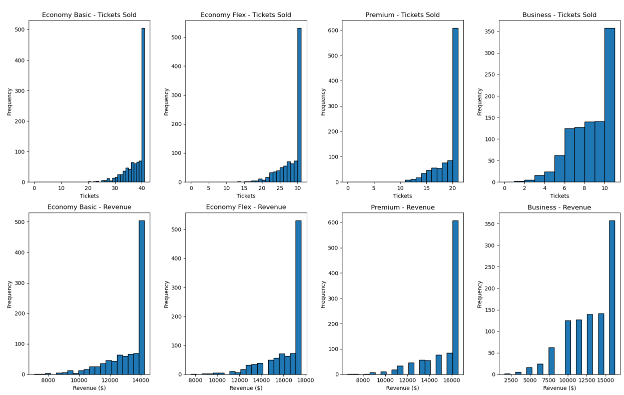

Figure 9: Final ticket sales and revenue histograms per fare bucket.

5.2 Final Revenue Distribution

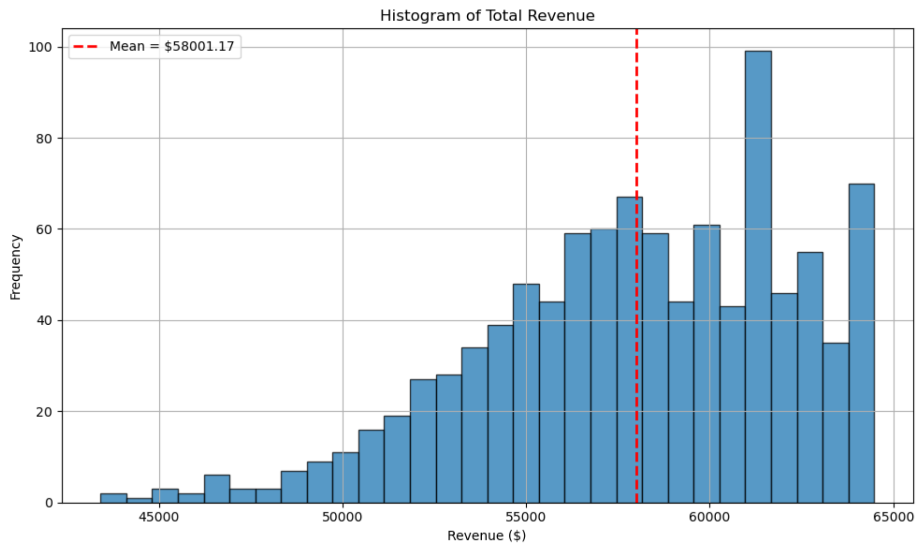

Figure 10: Final revenue distribution across trials. Mean revenue increased slightly, yet showed more variance.

6 Conclusions and Improvements

Overall, this project provided a clear introduction to the uses of Monte Carlo simulations in the real world to help understand complex, dynamic problems like airfare pricing. However, there are many enhancements we could make to the simulation design to improve results. Several such techniques are listed below which, given the necessary data, would improve simulation performance drastically:

6.1 Calibrating Base Demand with Real-World Data

One of the most critical assumptions in this simulation was the shape and scale of the base demand curves for each fare bucket. In future iterations, these curves should be informed by real airline booking data to reflect actual purchase patterns over time. Analyzing historical data by fare type, seasonality, and booking window would allow for more realistic and differentiated demand modeling, ultimately improving the validity of simulation results.

6.2 Rethinking Initial Price Selection

Initial fare prices were set arbitrarily in this model. However, in real-world scenarios, initial prices are strategically chosen based on competitor pricing, historical load factors, and forecasted demand. Future versions of this simulation could incorporate optimization techniques or historical data fitting to initialize fare prices more accurately, improving the realism and downstream pricing behavior.

6.3 Enhancing the Repricing Logic

In the current simulation, prices only adjust when ticket sales exceed expectations within a single day. This mechanism, while intuitive, lacks the granularity of modern pricing systems, which often respond to booking patterns over minutes or hours. A more realistic approach would involve incorporating short-interval transaction monitoring, rolling demand forecasts, and possibly stochastic control models to guide pricing updates more responsively.

6.4 Machine Learning-Based Price Adjustment

Rather than relying solely on rule-based logic, future work could involve training a machine learning or neural network model on historical ticket sale data to predict optimal price movements. Such models could take into account a variety of real-time inputs, such as booking speed, remaining time to departure, current fill rates, and competitor prices. These models could learn complex nonlinear patterns and outperform hand-coded heuristics in dynamic pricing contexts.

6.5 Fare Bucket-Specific Pricing Strategies

Different fare buckets serve different customer segments (e.g., leisure vs. business), and therefore behave differently under pricing pressure. Future simulations should assign each fare bucket its own repricing algorithm, tuned to its base demand profile and customer elasticity. For example, Economy Basic might benefit from slow-moving, volume-sensitive pricing, while Business Class may require sharp price increases in response to late-stage demand spikes.

7 Next Steps and Extensions

7.1 Exploring Multi-Flight or Network-Level Pricing

As an extension of this project, a valuable direction would be to scale the model to a network of interconnected flights. This would allow for joint optimization of pricing across legs, with considerations such as connecting traffic, shared capacity, and time-dependent rerouting of demand. This opens up a broader field of research into revenue management for airline networks rather than single flights.

7.2 Incorporating Cancellations and Rebookings

A further refinement would include modeling customer cancellations, refund policies, and rebookings. These behaviors impact final revenue, availability forecasts, and overbooking strategies, all of which are essential elements of a complete airline pricing system.